AFFECTIVE DIMENSIONS OF LEARNING

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Synonyms

Emotional Dimensions of Learning; Emotional Aspects in Learning; Emotional Factors in Learning

Definition

Affective Dimensions of Learning represents one of the three dimensions of learning identified by Illeris (2002). It is a complex concept that refers to dimensions for affective learning. According to Martin and Reigeluth, there exist six dimensions for affective learning: emotional, social, aesthetic, moral, spiritual and motivational (Martin and Reigeluth, 1999). In literature, the terms *Emotional Dimensions of Learning* and *Affective Dimensions of Learning* are often used to designate the relationship between emotions and learning (e.g. fears associated with formalized learning).

Although there is no consensus about the meaning of the term *emotion*, there is an agreement that emotional states are considered complex processes that change in time and are affected by several factors. An emotion represents a mental state, such as happiness or fear, that arises spontaneously rather than through conscious effort and is often accompanied by physiological changes. The majority of emotional theories concur that appraisals are necessary causes of emotions; however, there are divergent theories like James-Lange's theory which claims that emotion could arise due to physiological changes. This theory has been criticized by several recent researchers who think completely the opposite (Critchley, 2005). According to the appraisal theory, emotions arise from mental evaluation of events or situations depending on a person's goals (Ortony et al., 1988).

Theoretical Background

Some researchers in neurosciences and psychology (e.g. Damasio, 1994; Isen, 2000) have proved that emotions are widely related to diverse cognitive processes such as attention, long-term memorizing, problem solving, decision-making, etc. In fact, some studies have found that human beings tend to code more information if the tone of the material corresponds to their emotional states (Isen, 2000). For example if the learner is happy, he would encode more information when the material was also emotionally positive. Similarly, it has been demonstrated under various circumstances that human beings have a tendency to retrieve, from memory, information which is coherent to their current emotional states (Isen, 2000). For example if the learner is happy he would recall more easily happy material.

In addition, positive emotions are fundamental in learning processes; they play an important role to improve creativity and flexibility in problem solving and to enhance performance on the task at hand. They also may increase intrinsic motivation. However, negative emotions such as anxiety can give rise to disorders of attention, slow decision latency and deficit in inductive reasoning. They also have two types of effects: impairment effect related to reduced performance and bias effect related to prioritization of treating stimuli which have negative impact or valence (Matthews and Wells, 1999).

Mayer and Salovey defined emotional intelligence as: "ability to perceive accurately, appraise and express emotions; the ability to access and/or generate feelings when they facilitate thought; the ability to understand emotional knowledge; and the ability to regulate emotions to promote emotional and intellectual growth" (Mayer and Salovey, 1997). According to this definition, emotional intelligence is very important in learning environments. In the classroom, the teacher who has emotional intelligence abilities would maintain attention and learners interest by making jokes for example when he feels that his students are bored, he attempts to manage their emotional state in order to keep a good atmosphere for learning.

Because of the importance of emotional dimensions in learning and thought processes, several techniques for measuring emotion have been developed:

Self-report Techniques

This technique includes adjective checklists and a questionnaire-type scale. The adjective checklists consist of a series of adjectives describing the individual's current emotion for instance bored, joyful and sad. The challenge posed by this technique is choosing words that describe the current situation. The questionnairetype scale represents a set of questions related to emotional states. For example, to measure anxiety, the participants are asked to indicate their current feelings on a 4-point scale.

Facial Expressions

Emotional expressions have received great attention from both psychologists and computer science researchers interested in developing systems that detect emotions. Paul Ekman is among the first researchers who studied the expression of emotions. He created, along with his colleague Friesen, a system called FACS (*Facial Action Coding System*), which measures facial muscle movements (Ekman and Friesen, 1978). All subsequent research in the field is based on this pioneer work. In computer science, researchers have used various approaches to model the mechanism involved in the automatic detection of facial expressions. This mechanism consists of extracting and classifying facial characteristics. The extraction can be applied to the face entirely (considered like a whole), or locally, while focusing on the most expressive parts of the face, which depend on the facial expression itself.

Prosody Speech

The detection of emotion through voice analysis has not received as much attention from researchers as the detection of emotions using facial expressions. The first voice related work studied the contents of each word. Recently, researchers started investigating the prosodic and acoustic aspects, e.g. analyzing message features like intonation, duration, power, and articulation. Petrushin, for example, developed a system, geared towards call center applications, that uses voice to detect emotion in real-time using neural networks. His system can classify two emotions (calm and agitated) with 77% accuracy rate (Petrushin, 1999).

Physiological Changes

Another technique for detecting emotion consists of tracking physiological changes, for example, blood pressure, heart rate, skin conductance, muscle tension, etc. This technique is efficient when studying arousal, but is not as useful in detecting a specific emotion because it is very difficult to establish a relationship between physiological changes and specific emotions. On the one hand, some different emotions can have the same physiological changes. On the other hand, so many factors could trigger physiological changes that it would be difficult to link them to a given emotion.

In spite of the various approaches proposed to measure emotion, this task continues to be challenging in real scenarios. Human beings could have the same feelings but express them differently. This is why some researchers have combined different techniques to improve the automatic recognition of emotions. However, such methods for emotion detection present two limitations: (1) the use of sophisticated technology in a learning context can interfere with learning as noted by Picard who found that people may feel uncomfortable in the presence of video, cameras or physical sensors and that their presence may interfere with emotion recognition; and (2) it requires significant effort and financial resources. Thus, some researchers thought about considering the potential causes of emotions in the detection process.

Potential Causes of Emotions

Some psychology theories attempt to determine the origin of emotion by studying the relationship between cognition and emotion. Appraisal theories of emotion, in particular, consider that cognition is the core element in producing emotion (Ortony et al., 1988). They argue that emotion arises as a result of a cognitive evaluation of events or objects according to a person's goals and concerns. For example, let us take the case of a student who has just received an email indicating that he had passed a course. An emotion will occur following this situation according to his cognitive evaluation. If the event is important for the student's goals (to have the diploma), he may, for example, express joy. This evaluation is done according to some criteria or variables as defined in the appraisal models. For instance, in the OCC model, emotions are

regarded as valenced reactions (positive or negative) to environment perceptions. The environment in this model is composed of agents, events and actions. Thus, emotions arise as a consequence of:

- (1) whether the event is desirable or not (satisfaction/dissatisfaction);
- (2) approval or disapproval of the agent's actions (approval/disapproval);
- (3) love or rejection of some objects aspects (love/rejection).

In the OCC model, the authors define three criteria of evaluation:

- (1) goals which represent the criterion employed to evaluate events;
- (2) standards which represent the criterion employed to evaluate the agent's actions;
- (3) attitudes which represent the criterion employed to evaluate aspects of object.

All these criteria are used to indicate twenty two emotion types.

OCC model was the basis for most computational systems modelling emotion because of its effectiveness in simplifying the emotional states' representation. In addition, it offers clear and distinct evaluation criteria (goals, preferences and moral standards). This model provides a reliable representation of the virtual agents' emotions, but it is too general for modelling the user's emotion. Indeed, each individual exhibits different emotions following the same event. These reactions, according to Hess, depend not only on events, but also on several other factors such as sex, personality, current emotion, etc. Thus, emotions change over time in response to an emotional event and according to individual traits.

Important Scientific Research and Open Questions

Most existing learner models focus only on the learner's knowledge about the domain. However, the learner er model should describe both cognitive and emotional information about the learner. Emotional model should inform us about the emotional and the motivational state of the learner. It would focus on identifying the learner's emotional state in order to choose the right teaching strategy used by the tutor. In addition, during learning activities, we should pay attention to various factors that could trigger negative emotions. The tutor's role is then to intervene at the appropriate moment to alleviate the effects of these factors as far as possible and to adapt tutorial actions in order to stimulate positive emotions and achieve instructional goals. Initially, adapting tutorial actions in learning environment was mainly based on the learner's intellectual skills. Then, given the importance of emotions in cognitive processes and learning, selecting tutorial actions takes into account not only the cognitive state but also the emotional one which becomes an essential component of the learner's model (e.g. Chaffar et al., 2009; Conati, 2002).

The concept of *Emotional Dimensions of Learning* is sometimes so general that it raises and leaves many important questions:

- What emotions are relevant to learning?

- What emotions are good for learning?
- What are the best techniques to detect the learner's emotional state?
- What are the best methods for inducing good emotions for learning?

Cross-References

[Additional Related entries in the Encyclopedia of the Sciences of Learning; please find the complete list of all contributions at http://oesys.springer.com/ESL by going to "download <u>current List of Contributions</u> as a PDF document".

- \rightarrow Emotional Learning
- \rightarrow Anxiety, Stress and Learning
- \rightarrow Emotion-based Learning
- \rightarrow Learning by Feeling
- \rightarrow Learning to Feel

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